Urban Expansion and Pattern Analysis using Shannon's Entropy approach in ElMinya Governorate, Upper Egypt

Rania E. Ibrahim, Lamyaa G. Taha and Adel Shalaby

***Abstract*—**Urban expansion is a significant consequence of local land use/land cover change that is affected by human activities. Multi-temporal data enable monitoring urbanization over time in order to measure the changes of the urban expansion over the time interval. The aim of this research is to detect LULC changes in ElMinya governorate using Landsat TM /ETM/OLI satellite imageries for the years 1984, 2001 and 2017 respectively. The study uses Shannon's Entropy to monitor urban growth utilizing remote sensing and Geographic Information Systems. Firstly, the 1984, 2001 and 2017 imageries were rectified and co-registered to UTM projection with root mean square error 0.3, 0.37and 0.41 respectively. Secondly, land use/land cover maps were prepared for 1984, 2001 and 2017 using neural network algorithm with an overall accuracy of 94.4%, 96.2, 97.5% for 1984, 2001 and 2017 respectively. Imageries were classified using neural network classifier into four classes (water, agriculture, desert, urban). The study shows that there is a significant increase in urban area during the study period. The results indicated that urban area in 1984 was (10,456) hectare which has been increased to (17,596), (38,360) in 2001 and 2017 respectively. This increase attributed to the intensive urbanization. The agricultural land increased from (219,340) hectare in 1984 to (227,360), (262,021) in 2001 and 2017 respectively. The increase in agricultural land is attributed to reclamation activity. Thirdly, Shannon Entropy was computed to quantify the urban area for the whole governorate. The obtained Entropy value (0.191) in 2017 was higher than Entropy values (0.079), (0.121) in 1984 and 2001 respectively. Higher value of overall Entropy for the whole urban area gave an indication of urban growth (compact development). Also, Shannon Entropy was computed to quantify the urban area over each ward (markaz) in order to know which one has higher urbanization. It was found that the highest urbanization in Maghaghah. Lastly, the pattern of urban expansion was determined for each ward. It was found that the urbanization took place around existing urban areas for all wards.

***Keywords*—** *Neural Network, Shannon Entropy, Urban Expansion.*

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I. INTRODUCTION

Assessing and monitoring of land-use/land-cover (LULC) changes is critical for effective strategies of spatial management and environmental protection [1]. Urban expansion / growth defined as numerous natural land areas have been converted into urban areas by human activities [2]. Thus, the spatial location of the new construction will affect the process of urban expansion [3]. Extensive studies have mapped, analyzed, and modeled urban expansion process according to the spatial relationship between new construction and existing urban areas based on three urban types; infilling, edge expansion and outlying growth [3]-[6]. Infilling refers to new construction within/surrounding existing urban areas. Edge-expansion refers to new construction out from the peripherals of existing urban area. Outlying refers to expansion are widely separated from boundaries of existing urban areas and have no direct connection with the existing urban areas. The urban expansion process affects the ecosystem functions (i.e. social and economic mobility), and the sustainability of urban development which determines the future land use mixing level and infrastructure layout [4].

Numerous studies have been done to analyze LULC changes and urban growth, applying multiple tools and techniques, such as field work, aerial photographs and/or satellite imagery [7]-[12]. For any kind of sustainable development program (i.e. decision making) where LULC serves as one of the major input criteria, properly mapping LULC and its updates through time are essential for decision-making research [13]-[15]. For long temporal perspective, the best option to analyze LULC changes, determine urban growth is using Landsat data [1].

Shannon's Entropy acts as an indicator of spatial concentration or dispersion and can be used to investigate any geographical units. It is a statistical model whereby spatial variation and temporal changes of growth areas are taken into consideration to measure the spatial pattern of urban development. It can specify the degree of urban growth by examining whether the development is dispersed or compact [16]. The compact cities are more productive; that they deliver public services at a lower cost, that they enhance social and economic mobility, and that they improve health and well-being [17].

The general aim of land classification is detection and determining of changes in Earth's land cover [18]-[19]. Classifications can be organized as per-pixel, sub-pixel, object-oriented or per-field classifiers [20]. A large range of classification algorithms has been developed and applied for classifying remotely sensed data [21]-[22].

An Artificial Neural Network (ANN) can be viewed as a mathematical model composed of multiple computational neurons, operating in parallel and connected by weighted nodes [23]. The term topology refers to the structure of the network as a whole: the number of input, output, and hidden nodes and how they are interconnected [24]. The ability of ANN to simulate urban growth has been studied by [25]. ANN technique uses standard back propagation for supervised learning [26]. The learning uses back propagation to apply a layered feed-forward classification technique. The learning uses four hidden layers and a logistic activation function. The error is back propagated through the network and weight adjustment was made using a recursive method.

Change detection is the process of monitoring and interpreting differences in the state of object/phenomena by observing it over time [27]. Several Change detection techniques have been investigated such as image differencing, post-classification comparison, write function memory insertion etc. [28].

The post-classification comparison, sometimes referred to as ''delta classification'' involves independently produced spectral classification results from each end of the time interval of interest, followed by a pixel-by-pixel or segment-by-segment comparison to detect LULC changes [29]. Imageries belonging to different dates will be classified and labeled individually. Later, the classification results are compared directly and the area of changes extracted [27][30].

Morphological operators are used to extract structural information in spatial data [31]. Mathematical Morphology is a method to find out components that are proper for representation and description [32]. It is primarily used for binary image processing, but can also be used to support gray scale images [33]. Opening means smoothing the contour of an object, eliminating noises such as salt and pepper noise, and eliminating thin protrusions. Closing means fusing narrow breaks and long thin gulfs, eliminating small holes, filling gaps in the contour, and also smoothing sections of contours [32]-[35]. The opening operator was used to erase parts of objects or even objects smaller than the structuring element.

The objective of this research is analyzing urban expansion and pattern analysis of ElMinya governorate using Shannon's Entropy approach.

II. Study Area and Data Sources

ElMinya Governorate is located in Upper Egypt. It is located between 28° 47′ 52″ N and 32° 37′ 33″ E. ElMinya Governorate has been divided into 9 municipal wards (markaz) namely, Abu Qurqas, Bani Mazar, Dayr Mawas, Al Idwa, Minya, Mallawi, Maghaghah, Matay, Samalut. A total population of 2015 was 5,156,702 [36]. Figure 1 show location map of ElMinya Governorate.

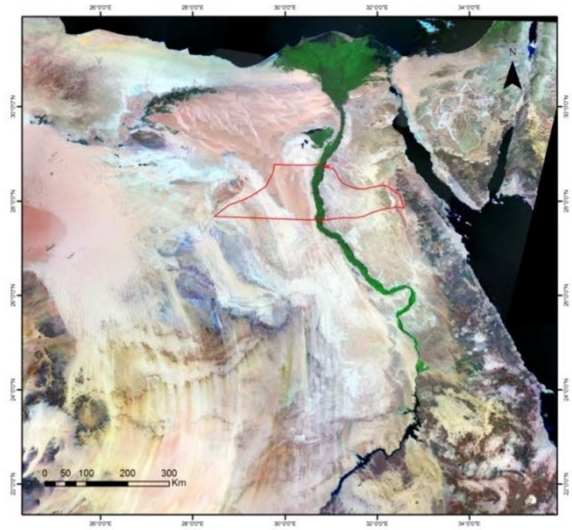


Fig. 1: Location map of ElMinya Governorate.

The data has been collected from primary and secondary sources (Table 1).

- LULC maps have been extracted from Landsat data acquired from three different sensors (Landsat-5 TM, Landsat-7 ETM+, and Landsat-8 OLI), for the years 1984, 2001 and 2017 respectively, which obtained from United States Geology Survey (USGS). They were used to prepare LULC maps and detect the spatiotemporal LULC changes of the study area, taking into account seasonal differences and imagery quality (cloud-free).
- Thirty well distributed differential GPS control points have been obtained with 10 cm accuracy in x,y,z.

Table 1. Different types of data used.

S. no.	Type of data	Resolution	Year
1	Landsat-5 TM	30m	1984
2	Landsat-7 ETM+	30m	2001
3	Landsat-8 OLI	30m	2017
4	Ground control points(GPS) and check points	30 points	
5	Topographic maps	1:50000	
6	Boundary map		

III. Methodology

In this section, the processing chain that has been carried out for LULC changes monitoring over three dates 1984, 2001 and 2017 of Landsat imageries was discussed. The processing steps were as follows (Fig. 2):

- Imagery pre-processing (i.e. layer stacking) was implemented using ENVI 5.1.
- Atmospheric correction was applied using quick atmospheric correction module in ENVI 5.1.
- Landsat imageries of 2017 were rectified using second order polynomial utilizing fifteen well-distributed

differentia GPS control points and checked using fifteen well-distributed differentia GPS control points (in ENVI 5.1).

- Landsat imageries of years 1984, 2001 have been co-registered with Landsat 2017 using second order polynomial in ENVI 5.1.
- Classifications of optical bands for multi-temporal imageries have been performed using the neural network techniques in ENVI 5.1. The classified maps were checked with overall accuracy and kappa index.
- Morphological operators were performed. Morphological opening was performed followed by morphological closing.
- Changes in LULC during the different periods were detected(1984 -2001/2001-2017/1984–2017)
- Urban areas of each markaz of ElMinya and the total area of each markaz (area of administrative boundary of the markaz is constant for the three years) have been computed for the three dates.
- Shannon's Entropy has been computed for each markaz and for the whole governorate.
- Pattern of urban growth was identified.

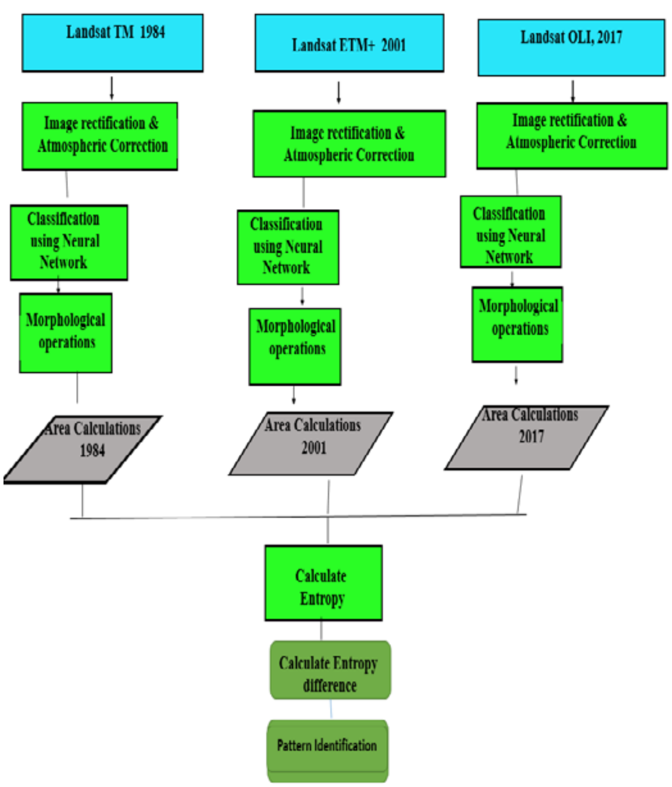


Fig. 2: Methodology Framework.

A. Imagery Preprocessing

Firstly each OLI/TM/ETM file, layer stacking tool was applied to combine the single-band imageries into a multi-bands imagery of OLI/TM/ETM excluding the thermal band. Secondly atmospheric correction was applied using quick atmospheric correction module in ENVI 5.1 as a pre-processing step.

B. Imagery Rectification

Landsat 2017 imagery has been rectified using well distributed fifteen differential GPS control points (roads intersections). A second order polynomial model was chosen for the rectification and the imagery was resampled using the nearest neighbor algorithm with a pixel size of 30 *30 m. The resultant RMS of the fifteen differential GPS check points was less than 0.3 pixels.

C. Imagery Co-registration

Change detection analysis was performed on a pixel-by-pixel basis; therefore any mis-registration greater than half pixel will provide an anomalous result of that pixel. To overcome this problem, the RMSE between any two dates should not exceed 0.5 pixels [7][37].

All other Landsat satellite imageries were co-registered to a common Universal Transverse Mercator (UTM) projection using second order polynomial based on Landsat 2017 reference imagery. The resultant RMS of the fifteen differential GPS check points was less than 0.45 pixels for all other imageries (1984, 2001).

D. LULC classification

Classification is the process of organizing and arranging pixels (based on their data file values) into a finite number of individual classes [38].

The neural network classification method was conducted for classifying the different Landsat imageries into four LULC categories, namely, Urban, Agriculture land, Desert land and Water. Urban includes buildings, roads, etc. Agriculture land includes all areas used for agriculture such as field crops, trees, etc. Dessert land includes lands without any cover such as bare land, dessert, etc. Water includes all bodies of water such as lakes, rivers, or canals. Signatures has been collected and evaluated. The neural network classifier was chosen for spectral classification of the Landsat imageries dependent on the collected training data. The Classification was implemented in ENVI 5.1. Afterward, post-classification refinements were used to reduce classification errors. The classified imageries were exported to the ArcGIS 10.2 software for vectorization and calculation of areas for the different dates and to identify changes of LULC.

E. Classification Accuracy Assessment

Classification accuracy was assessed using the error matrix, including overall accuracy and the Kappa statistic [39]. The overall accuracy was 94.4%, 96.2 %, 97.5% for 1984, 2001 and 2017 respectively. Kappa coefficient was 0.86, 0.92 and 0.97 for 1984, 2001 and 2017 respectively.

A morphological opening filter using kernel size 3 x 3 was applied to the classified imageries followed by morphological closing filter in order to remove small elongated objects such as fences and to separate regions just bridged by a thin line of pixels.

F. Shannon's Entropy approach

Shannon's Entropy measures the patterns of urban area either dispersed or compact over time [40]-[41]. In this research, the Entropy approach was applied for quantifying the urban growth over ElMinya governorate. Also, Entropy was used for quantifying the urban growth over each markaz. It was taken as the base for the evaluation of the urban spatial pattern for 1984, 2001 and 2017.

Shannon's Entropy(Hn) was given by [40][42].

$$Hn= -\Sigma P_i \log_e (Pi)$$

Where;

Pi: is the proportion of the variable in the i^{th} zone or refers to the area in i^{th} markaz.

Entropy value ranges from 0 to Log (n), Where n represents the total number of wards (markaz) and Log (n) =Maximum limit of Entropy. Due to the availability of data for only 9 markaz, the upper limit of Entropy is (1). Here, if the value is closer to zero, the distribution is very compact. If the value closer to Log (n), the distribution is dispersed [16][41][43].

IV. Results and Discussion

A. Assessing urbanization degree

The current study has assessed LULC changes and spatial expansion of urban areas in ElMinya using satellite imageries for the years 1984, 2001, 2017. Four LULC classes were identified and mapped for the three time periods. Figure3 depicts LULC maps of ElMinya (1984, 2001, 2017). The overall accuracy was 94.4%, 96.2 %, 97.5% for 1984, 2001 and 2017 respectively. Kappa coefficient was 0.86, 0.92 and 0.97 for 1984, 2001 and 2017 respectively. The classification maps obtained by ANN classification followed by morphological operations were less noisy than the classification maps obtained by the neural network classification only. Table 2 show changes of LULC for all wards of ElMinya governorate for 1984, 2001, 2017.

It is clear that urban areas of ElMinya governorate have been increased from (10,456) ha in 1984 to (17,596), (38,360) in 2001 and 2017 respectively. This increment attributed to the intensive urbanization (Fig. 4).

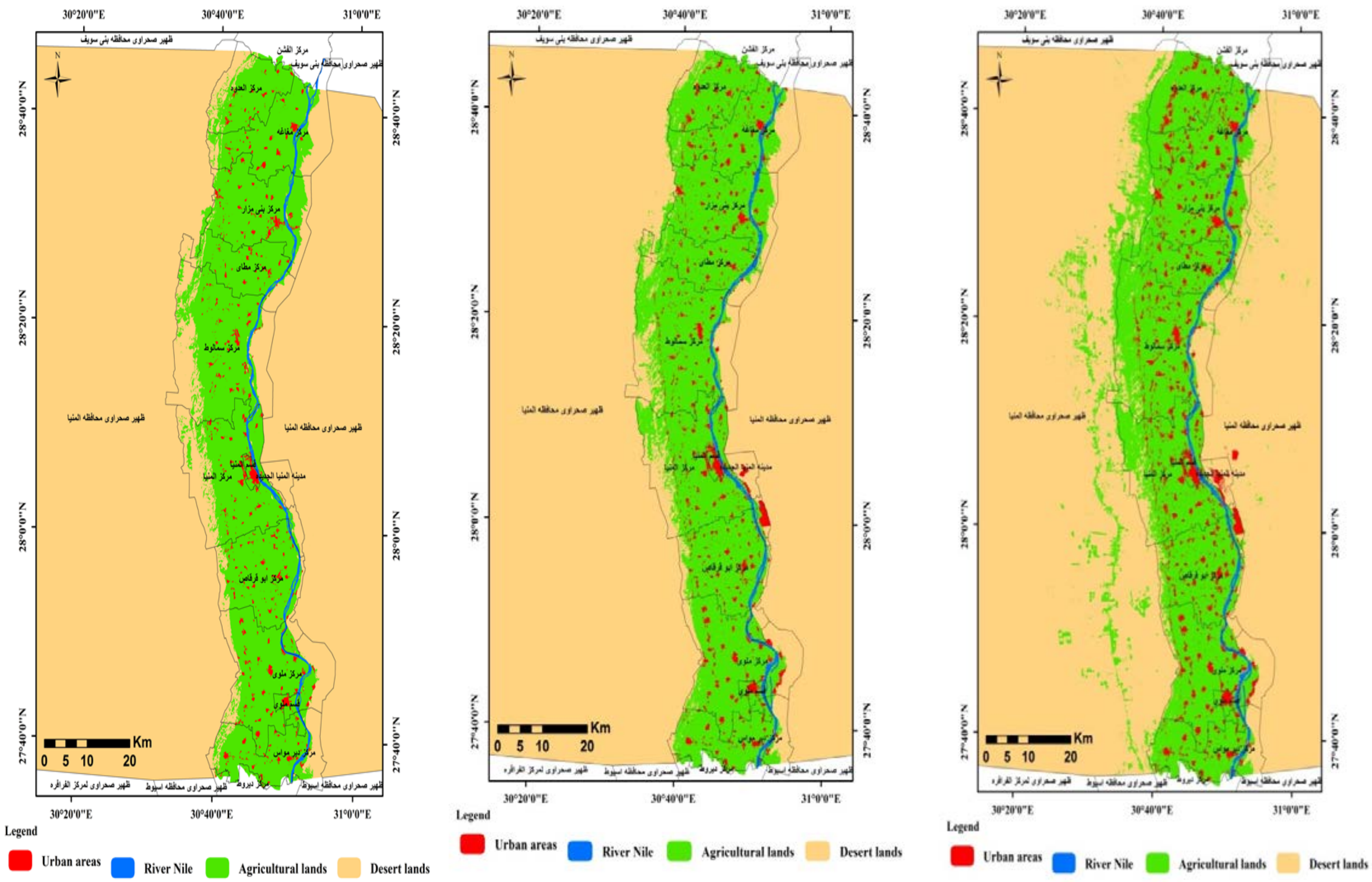
The agricultural land has been increased from (219,340) ha in 1984 to (227,360), (262,021) in 2001 and 2017 respectively. This increase is due to reclamation activity. Based on Fig. 3, it is clear that the increment in agriculture have been observed in the west of the core (desert).

From Table 2, the urban areas has been increased by (27,904) ha from 1984 to 2017, this revealed that the main reason of urban expansion was the land transformation from agriculture and desert lands to urban. Most of the small villages in Egypt suffer from shortage of land appropriate for urban development, so urban expansion happens on agricultural lands because of the increasing demand for housing units as well as social services due to the growing young population which requires either the transformation of agricultural lands into urban areas or increasing the population density within the existing urban boundaries of villages. On the other hand, it is difficult to increase the urban densities due to restrictions on building heights. Moreover, Agriculture lands in the small villages are usually fragmented into small non-economic land slots which do not generate satisfied income for owners. Both factors lead to urban sprawl over agricultural land which is mostly informal, unplanned and consume fertile agriculture lands. Subsequently and in order to accommodate the growing urban population, the government extends ElMinya to desert areas (Zaher Sahrawy) starting from the year 2013.

B. Shannon's Entropy model for urban growth

Entropy values have been calculated across all wards (Table 3), and are summed-up to represent the Entropy for the whole urban area. Based on Table 3, it is apparent that, Entropy value has been increased from (0.079) in year 1984 to (0.121), (0.191) in 2001 and 2017 respectively. Larger value of Entropy (0.191) in 2017 compared to the ones in 1984 and 2001 reveals the occurrence and spatial distribution of urban expansion is compact because it is near the lower limit. Relatively lower value of Shannon's Entropy(0.079) in the year 1984 indicated the concentration and homogeneous distribution of urban area. Urban expansion has occurred in all the wards in compact way.

By comparing the Entropy values for 9 markaz, it was found that Maghaghah has higher value of entropy, which increased by (836) ha between 1984 and 2001 and further increased by (1861) ha between 2001 and 2017. The pattern of urban growth in each ward of the 9 wards was surround existing urban area. Thus, it can be concluded that Shannon's Entropy was useful and effective in identifying the urban expansion phenomenon.



1984 2001 2017

Fig. 3: Classified maps for LULC classes of study area.

Table 2. Changes of LULC classes for all Markaz of ElMinya governorate for years 1984, 2001, 2017.

Markaz	Built-up area (ha)			Change area (ha)			Agriculture area (ha)			Change area (ha)			Desert area (ha)			Change area (ha)		
	1984	2001	2017	1984-2001	2001-2017	1984-2017	1984	2001	2017	1984-2001	2001-2017	1984-2017	1984	2001	2017	1984-2001	2001-2017	1984-2017
Abu Qurqas	1237	1884	3348	647	1464	2111	24777	24692	23978	-84	-714	-799	3442	2637	1833	-805	-804	-1608
Bani Mazar	1234	1793	4523	559	2730	3289	25791	25875	24825	84	-1050	-966	3332	2655	978	-678	-1677	-2355
Dayr Mawas	1234	1213	2008	-20	795	774	25791	16332	16078	-9459	-254	-9713	3332	3925	3393	593	-533	60
Al Idwa	472	1060	2120	588	1059	1647	14403	16547	16662	2144	116	2260	4519	1285	112	-3234	-1173	-4407
Minya	1799	4003	7675	2204	3672	5876	29758	39226	33150	9468	-6076	3392	14805	10376	5536	-4429	-4840	-9269
Mallawi	1823	2919	4746	1096	1828	2924	28613	29141	28667	529	-475	54	9264	7639	6281	-1625	-1357	-2983
Maghaghah	886	1722	3583	836	1861	2697	21214	21431	21815	217	385	602	7262	6105	3843	-1158	-2261	-3419
Matay	580	883	2213	303	1330	1633	15451	15920	16123	469	203	672	3888	2961	1414	-927	-1547	-2474
Samalut	1192	2107	5712	915	3605	4521	32707	36007	37412	3300	1405	4705	17431	13114	8079	-4317	-5035	-9352
Zaher Sahrawy	0	11	2431				836	2190	43310				2581910	2537004	2537004			
Total	10457	17595	38359	7128	18344	25472	219341	227361	262020	6668	-6460	207	2649186	2587701	2568474	-16579	-19227	-35806

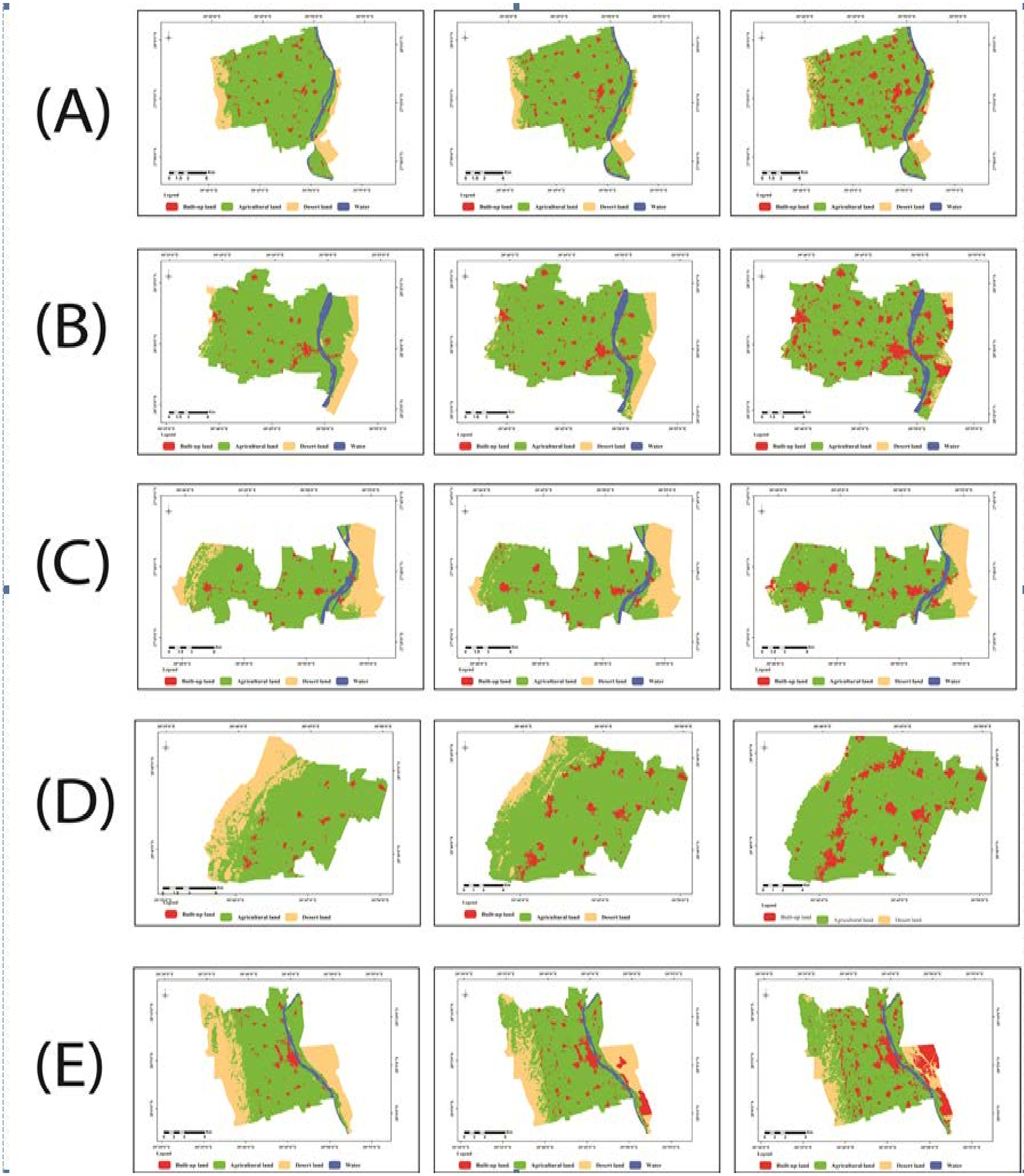


Fig. 4: Changes in LULC in 9 Marakaz: a) Abu Qurqas, b) Bani Mazar, c)Dayr Mawas, d) Al Idwa, e)Minya.

Fig. 4: Changes in LULC in 9 Marakaz: f)Mallawi, g)Maghaghah, h)Matay, i) Samalut.

Table 3. Calculated Entropy values.

Markaz name	**pi**								
	1984	**2001**	**2017**	**Log1984**	**Hn1984**	**Log2001**	**hn2001**	**log2017**	**hn2017**
Abu Qurqas	0.002	0.003	0.005	2.693	0.005	2.510	0.008	2.261	0.012
Bani Mazar	0.001	0.001	0.0021	3.190	0.002	3.028	0.003	2.626	0.006
Dayr Mawas	0.001	0.001	0.001	3.090	0.003	3.097	0.002	2.878	0.004
Al Idwa	0.00041	0.00091	0.002	3.36	0.001	3.008	0.003	2.707	0.005
Minya	0.001	0.002	0.005	2.950	0.003	2.603	0.006	2.320	0.011
Mallawi	0.0011	0.002	0.004	2.812	0.004	2.607	0.006	2.396	0.01
Maghaghah	0.041	0.079	0.165	1.389	0.057	1.1004	0.087	0.782	0.129
Matay	0.001	0.001	0.002	3.293	0.002	3.111	0.002	2.711	0.005
Samalut	0.001	0.0014	0.004	3.110	0.002	2.863	0.004	2.430	0.009
Total of Gov.					0.079		0.121		0.191

V. Conclusion

The urban growth of ElMinya governorate over a period of nearly thirty three years was quantified in terms of the changes in urban areas as well as Shannon's Entropy. The study has demonstrated that integrated use of remote sensing and GIS techniques can assess and quantify the nature, rate and extent of LULC changes and thereby contribute towards an improved understanding of the process of LULC changes.

The standard image processing techniques such as, rectification, co-registration, and classification were applied in the current study. LULC maps were performed using neural network classification for the years 1984, 2001, 2017. The overall accuracy was found 94.4%, 96.2 %, 97.5% for 1984, 2001 and 2017 respectively. Kappa coefficient was 0.86, 0.92 and 0.97 for 1984, 2001 and 2017 respectively.

The results revealed that urban areas have expanded more than three folds during the study period mainly on the expense of fertile agricultural land. The highest urbanization has occurred in Maghagha. The agricultural land has also been increased due to reclamation activity and this increment has been observed mainly in the west.

Shannon Entropy approach acted as a good indicator for measuring the spatial pattern of urban expansion. The Entropy values for urban areas were 0.079, 0.121, and 0.191 in 1984, 2001, 2017 respectively, indicating a compact development over all markaz. The results show the pattern of urban growth was surround existing urban areas. The results could be useful for urban planners, decision makers and also for understanding the future trends of urbanization.

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